MALAYSIAN LICENSE PLATE RECOGNITION ALGORITHM USING CONVOLUTIONAL NEURAL NETWORK

MUHAMAD MARZUKI BIN PIRAMLI

MASTER OF SCIENCE IN ELECTRONIC ENGINEERING

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Electronics and Computer Engineering

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MUHAMAD MARZUKI BIN PIRAMLI

A thesis submitted
in fulfillment of the requirements for the degree of Master of Science
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DECLARATION

I declare that this thesis entitled “Malaysian License Plate Recognition Algorithm Using Convolutional Neural Network” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature : ……………………………………

Name : **Muhamad Marzuki bin Piramli**

Date : **24 Oktober 2020**

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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronic Engineering.

Signature : ……………………………………….

Supervisor Name : **Dr. Syafeeza bt Ahmad Radzi**

Date : **24 Oktober 2020**

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DEDICATION

Dedicated to my beloved parents.

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ABSTRACT

Nowadays, License Plate Recognition (LPR) becomes popular among researchers due to its compatibility in many applications. For instance, LPR significantly can be applied to toll gate systems, surveillance systems and law enforcement. However, the previous LPR system still does not meet optimum accuracy and speed. Current Convolutional Neural Network (CNN) improvements have the ability to solve complex visual recognition tasks. The primary aim of this system is to ensure that the character of the vehicle plate recognize accurately and efficiently using CNN techniques. A method utilizing two CNN network architectures of deep object detection was designed to solve the Malaysian License Plate Recognition (MLPR) task. The first and the second network were designed for plate detection and recognition of license plate characters respectively. Both of the networks utilized the architecture of YOLOv2 with high speed and accuracy. The accuracy and speed of the plate recognition of the MLPR obtained were 98.75% and 0.0104 seconds respectively. The MLPR has obtained high prediction accuracy and has outperformed the existing methods. In conclusion, the system adapted from deep object detection is the best solution for the MLPR problem based on the accuracy and speed achieved.

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ALGORITMA PENGECAMAN NOMBOR PLAT MALAYSIA MENGGUNAKAN RANGKAIAN KONVOLUSI NEURAL

ABSTRAK

Pada masa kini, Pengecaman Plat Lesen (LPR) menjadi popular di kalangan penyelidik-penyelidik disebabkan keserasiannya dalam pelbagai aplikasi. Contohnya, LPR boleh digunakan pada sistem tol, system tinjauan dan penguatkuasaan undang-undang. Namun, sistem LPR yang sedia ada tidak mencapai ketepatan dan kelajuan yang optimum. Peningkatan keupayaan Lingkaran Rangkaian Neural (CNN) yang terkini mempunyai kemampuan dalam menyelesaikan pengecaman visual yang rumit. Objektif utama sistem ini dibangunkan adalah untuk memastikan pengecaman plat kenderaan dengan lebih tepat dan cepat menggunakan teknik CNN. Satu kaedah yang menggunakan dua senibina CNN bagi pengecaman objek direkabentuk bagi menyelesaikan tugasan pengecaman plat Malaysia (MLPR). Rangkaian pertama dibangunkan untuk pengecaman kawasan yang mengandungi plat dan rangkaian kedua untuk pengecaman bagi ciri plat. Kedua-dua rangkaian menggunakan seni bina YOLOv2 dengan ketepatan dan kelajuan yang tingggi. Ketepatan dan kelajuan pengecaman plat bagi MLPR masing-masing adalah 98.75% dan 0.0104 saat. *MLPR telah mencapai ketepatan ramalan yang tinggi dan mengatasi kaedah yang sedia ada. Kesimpulannya, sistem yang diadaptasi daripada pengecaman objek mendalam adalah penyelesaian terbaik untuk masalah MLPR berdasarkan ketepatan dan kelajuan yang telah dicapai.*

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LIST OF ABBREVIATIONS

2D	-	Two Dimension
3D	-	Three Dimension
AlexNet	-	Alex Network
AI	-	Artificial Intelligence
AOLP	-	Application Oriented License Plate
CIFAR-10	-	Canadian Institute For Advanced Research Dataset
CNN	-	Convolutional Neural Network
CPU	-	Computer Processing Units
Darknet19	-	Unsupervised Learning
DPM	-	Deformable Part Models
FCN	-	Fully Convolutional Network
FPS	-	Frame Per Second
GoogLeNet	-	Foundation of DeepDream
GPU	-	Graphical Processing Units
HOG	-	Histogram of Oriented Gradients
HSV	-	Hue Saturation Value
ILSVRC	-	Imagenet Large Scale Visual Recognition Competition
iOS	-	Iphone Operating System
IOU	-	Intersection Over Union
LeNet5	-	LeCun Network 5

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LP	-	License Plate
LPR	-	License Plate Recognition
MLPR	-	Malaysian License Plate Recognition
mAP	-	Mean Normal Accuracy
MSE	-	Mean Square Error
OCR	-	Optical Character Recognition
OpenCV	-	Open Computer Vision
R-CNN	-	Region CNN
ReLU	-	Rectified Linear Network
ResNet	-	Residential Network
RGB	-	Red Green Blue
RNN	-	Recurrent Neural Network
RoIPool	-	Region Of Interest Pooling
ROLO	-	Recurrent YOLO
RPN	-	Region Proposal Network
SIFT	-	Scale-Invariant Feature Transform
SVM	-	Support Vector Machines
TDNN	-	Time-Delay Neural Networks
VGGNet	-	Visual Geometry Group Network
VOC	-	Visual Object Classes
WTW	-	AS Dataset
YOLO		You Only Look Once
YOLOv2		You Only Look Once (Version 2)

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LIST OF PUBLICATIONS

i. P. Marzuki, A.R. Syafeeza, Y.C. Wong, N.A. Hamid, Z. M. Noh, 2019. A Design of License Plate Recognition System Using Convolutional Neural Network. *International Journal of Electrical and Computer Engineering (IJECE), 2018 3rd Engineering Technology International Conference*. 9 (3), 2196. (Indexed Scopus).

ii. M.M. Piramli, A.F.N.A. Rahman, S.F. Abdullah, 2016. Rice Grain Grading Classification Based On Perimeter Using Moore-Neighbor Tracing Method. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 2016 8th International Conference*, pp. 23-27. (Indexed Scopus).

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CHAPTER 1

INTRODUCTION

1.1 Research background

Nowadays, the quantity of vehicles on the roads has radically expanded. With this growth, it is extremely hard to monitor every vehicle in order to include smooth traffic movement for law enforcement purposes (Jain et al. 2016). License Plate Recognition is utilized progressively these days for automatic toll gathering, keeping law enforcement and traffic activity. Numerous techniques of license plate recognition been proposed, but still have their own particular advantages and disadvantages. This project focused on the issue of Malaysian car license plate detection and recognition in natural scene images.

Based on the excellent achievement of deep Convolutional Neural Networks (CNN) in different vision applications, CNNs are utilized in order to learn high-level features to enhance the performance of Malaysian License Plate Recognition (MLPR). The complicated image background can also be a challenging task such as signboard, bricks, guardrail, and text-like outlier. The overall MLPR system consists of plate detection and plate character recognition. The operation of plate detection includes localizing or predict the plate region to generate a bounding box accurately resulting in a cropped plate region. While plate character recognition predicts the character of the license plate within the bounding boxes region.

Malaysian License Plate Recognition (MLPR) system captures the vehicle license plate image and extracts the bounding box of the license plate. The extracted bounding box is then further extracted into alphanumeric characters for recognition. These alphanumeric

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characters are compared to one or more databases to identify the vehicle's license plate number. A typical LPR system flow is as the following:

i. Plate detection: finds and isolates the license plate region from the captured image by the camera.
ii. Character segmentation: extracts the alphanumeric characters from the license plate.
iii. Character recognition: recognizes the license number of the vehicle.

1.2 Problem statements

The license plate recognition (LPR) is a significant research interest parallel with current intelligent transportation systems technology. Many research works were carried out to improve the LPR but most of them only work under controlled conditions to ensure the optimum recognition accuracy in a challenging situation. Figure 1.1 shows the examples of captured license plates dataset with challenging conditions only focus on MLPR.

(a) Illumination

(b) Improper angle

(c) Blurring

(d) Dirty plate

Figure 1.1: Examples of the challenging condition of license plate

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A deep learning algorithm should be developed to improve the accuracy and speed of the recognition of license plate characters. Previous LPR system still does not meet optimum accuracy in challenging condition and lack of robustness using Malaysian plate.

1.3 Research questions

The main objective of this research is to develop an MLPR using Convolutional Neural Network (CNN) that can be applied in real-world applications to handle high uncertainty cases faced by previous methods. The evaluation of this project made based on prediction accuracy and processing speed. There are three research questions analyzed as follows

i. How to design the CNN algorithm for license plate detection and recognition problem?

ii. Does the proposed system reach the accuracy and processing speed in MLPR implementation?

1.4 Research objectives

A research objective that is related to each research question is created to achieve the research aims. There are two research objectives identified in this research that are as follows:

i. To design a CNN algorithm for the license plate recognition system classification of alphanumeric characters.

ii. To evaluate the performance in terms of accuracy of the CNN algorithm as a solution for the Malaysian license plate detection and recognition problem.

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1.5 Scopes

In this research, a CNN is utilized as a classifier and feature extractor to recognize all numbers (0-9), alphabets (A-Z) by separate CNN models. Graphics Processing Units (GPU) is used to ensure high-performance computing especially in the computer vision, machine learning field to solve the challenging problems. CNN's include lots of computation which includes storage of model variables on memory. To speed up executions, high-speed memory access is required in order to simulate neural networks as normal CPU takes a lot of time for training the network. In this project, CNN has been implemented TESLA K40c GPU. TESLA K40c was among advanced GPU powered by NVIDIA architecture. The hardware used for training CNN is installed with Ubuntu 14.04 which runs on Intel Xeon(R) processor. The processor clock speed is 2.4 GHz and consists of 8GB RAM.

The approach utilizes two large CNN which consist of plate region detection and recognition network. About 270MB of memory space must be allocated for every trained CNN, including to all relevant code less than 500MB. As much as 6.5GB of storage space is needed to run both modules. The separate modules run independently may decrease the GPU requirements. YOLO and Darknet are main dependencies in this project and OpenCV 2.8 is an additional dependency.

Each country has its own specific license plate patterns. For example letters numbers, background color, position and font style. In this project, about 2400 standard Malaysian license plate was captured in the parking area as shown in Figure 1.2. The RGB image with 640×480 resolution was used as a training and test set in improving Malaysian License Plate Recognition (MLPR). For recognition experiments, the dataset split into two training and testing samples. For all the experiments, consider 68% for training, 16% for validating and 16% for testing of the datasets.

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Figure 1.2: Malaysian standard license plate

The detection of plates might be harder for MLPR since the training set might not contain numerous similar cases. Based on most of Malaysian license plates cases, there are several variations that may affect the detection and recognition task.

1.6 Significance of research

This project proposed a design technique comprising of two deep CNNs of object detection implemented in LPR using the Malaysian license plate. Two networks used in MLPR were Plate Detector and Plate Recognizer respectively. By adapting the object detection approach in MLPR, high accuracy was obtained using parked cars images as a test set, which is robust to challenging image condition. Moreover, the MLPR outperforms to other methods and relevant to implement in a real-world application such as a toll surveillance system to improve security.

1.7 Thesis organization

This thesis consists of six chapters. Chapter 1 determines the research background, related issues, objectives, problem statements, scopes of work, and research contributions. Chapter 2 clarify the basic concept of the Convolutional neural network (CNN) and reviews

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other previous work on detection, segmentation and recognition of the Malaysian license plate. Chapter 3 discusses more details about the methodology used to highlight the research contributions and the implementation of Malaysian license plate recognition CNN. Chapter 4 discusses and justifies the experiment and results of CNN in MLPR problems. Lastly, Chapter 5 summarizes and concludes the overall research work, restating the research contributions and future works recommendation.

1.8 Summary

This project is developed based on the problem statements, questions, objectives and scopes to enhance the performance of License Plate Recognition (LPR) using Malaysian Plate. Most of the existing method has limited accuracy and robustness in challenging condition. Thus, the design and development of the CNN algorithm should be carried out to enhance the robustness and accuracy of MLPR. The research only focusses on the Malaysian license plate and all scopes have been explained clearly in this section. The next chapter will describe the CNN theory which explained the CNN concept in detail.

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